Neural Network for Image Segmentation

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ABSTRACT

Image analysis is an important requirement of many artificial intelligence systems. Though great effort has been devoted to inventing efficient algorithms for image analysis, there is still much work to be done. It is natural to turn to mammalian vision systems for guidance because they are the best known performers of visual tasks. The pulse-coupled neural network (PCNN) model of the cat visual cortex has proven to have interesting properties for image processing. This article describes the PCNN application to the processing of images of heterogeneous materials; specifically PCNN is applied to image denoising and image segmentation. Our results show that PCNNs do well at segmentation if we perform image smoothing prior to segmentation. We use PCNN for both smoothing and segmentation. Combining smoothing and segmentation enable us to eliminate PCNN sensitivity to the setting of the various PCNN parameters whose optimal selection can be difficult and can vary even for the same problem. This approach makes image processing based on PCNN more automatic in our application and also results in better segmentation.

Keywords: pulse-coupled neural network, PCNN, image processing, segmentation, smoothing, granular materials.

1. IMAGE PROCESSING WITH PULSE-COUPLED NEURAL NETWORKS

A PCNN is a biologically inspired algorithm for image processing. [1,2] It is to a very large extent based on Eckhorn's model of the cat visual cortex.[3,4] The typical neuron of a PCNN is shown in Fig. 1. The equations for a single iteration of the PCNN are

$$
\begin{aligned}
F_{ij}[n] &= e^{-\alpha_F} F_{ij}[n-1] + S_{ij} + V_F \sum_{kl} m_{ijkl} Y_{kl}[n-1] \\
L_{ij}[n] &= e^{-\alpha_L} L_{ij}[n-1] + V_L \sum_{kl} w_{ijkl} Y_{kl}[n-1] \\
U_{ij}[n] &= F_{ij}[n](1 + \beta L_{ij}[n]) + I \\
Y_{ij}[n] &= \begin{cases} 1, & if\ U_{ij}[n] > \Theta_{ij}[n] \\ 0, & otherwise \end{cases} \\
\Theta_{ij}[n] &= e^{-\alpha_\Theta} \Theta_{ij}[n-1] + V_\Theta Y_{ij}[n]
\end{aligned} \tag{1}
$$

where S is the input signal, F is the feed, L is the link, U is the internal activity, Y is the pulse output, and Θ is the dynamic threshold. The weight matrices M and W are local interconnections and β is the linking constant. I is the inhibition term that is determined by the total activity of the network. The output values of all neurons are summed up, negated, and fed back to each neuron of the neural network.

The basic simplified structure of the pulse-coupled neural network processor for a two-dimensional input image is shown in Fig. 2. An input gray-scale image is composed of $M \times N$ pixels. This image can be represented as an array of $M \times N$ normalized intensity values. Then the array is fed in at the $M \times N$ inputs of PCNN. If initially all neurons are set to 0, the input results in activation of all of the neurons at a first iteration. The threshold of each neuron, Θ, significantly increases when the neuron fires, then the threshold value decays with time. When the threshold falls below the respective neuron's potential (U), the neuron fires again, which again raises the threshold. The process continues creating binary pulses for each neuron.

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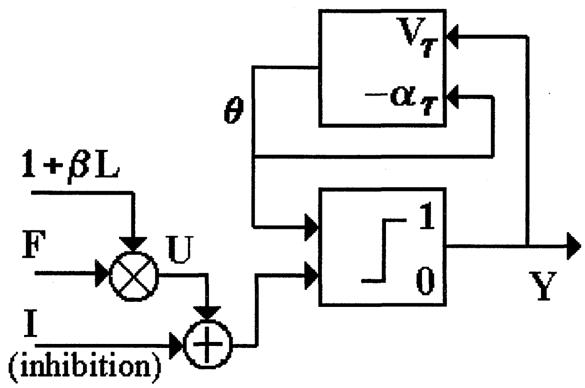

Fig. 1. The basic PCNN neuron.

While this process goes on, neurons encourage their neighbors to fire simultaneously in a way that is supported through interconnections. The firing neurons begin to communicate with their nearest neighbors, which in turn communicate with their neighbors. The result is an autowave that expands from active regions. Thus, if a group of neurons is close to firing, one neuron can trigger the group. Due to linking between neurons, the pulsing activity of invoked neurons leads to the synchronization between groups of neurons corresponding to subregions of the image that have similar properties and produces a temporal series of binary images. This synchronization results in image segmentation.

The success of the application of PCNNs to image segmentation depends on the proper setting of the various parameters of the network, such as the linking parameter β, thresholds Θ, decay time constants τ, and the interconnection matrices M (m_{ijkl}) and W (w_{ijkl}). Proper setting of the parameters is especially important when intensity significantly varies across a single segment. In this case, segmentation can result in different sequences of binary images depending on the network's settings. Decreasing this type of dependence of the results on the parameters settings can make PCNN image processing more efficient. We decrease this dependance by combining smoothing and segmentation. First, we perform PCNN-based smoothing, then we perform segmentation using PCNN.

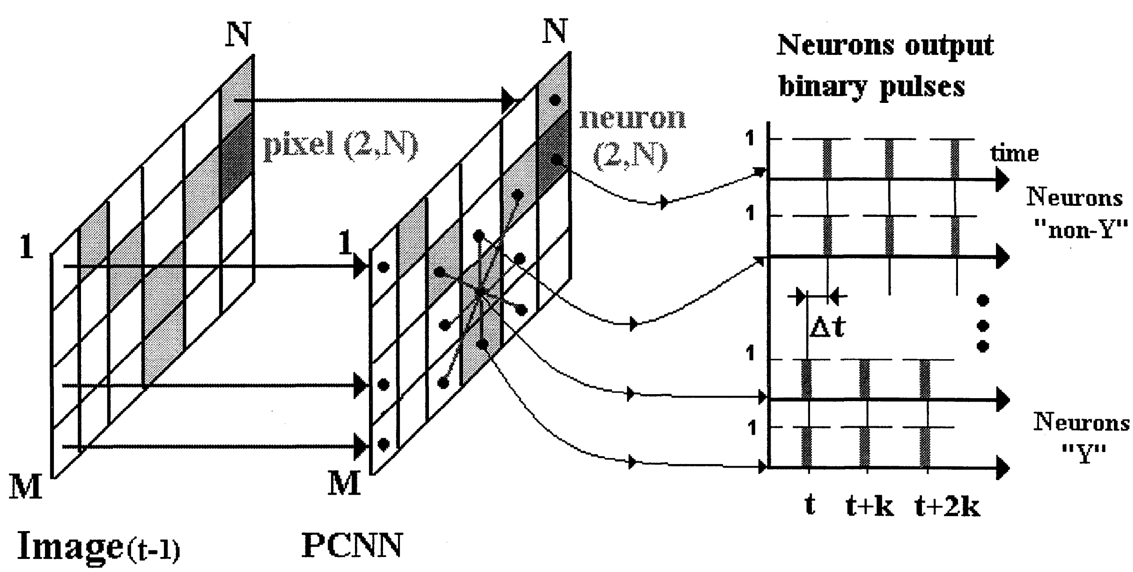

Fig. 2. Image processing using a pulse-coupled neural network.

PCNN smoothing is achieved through iterated modification of the original intensity levels of an input image. Adjustment of a pixel's intensity depends on the temporal history of how neighboring pixels fire. If a given pixel does not fire simultaneously with the majority of its neighbors, then its intensity is examined. If a pixel fires after the majority of its neighborhood, its intensity is increased, otherwise it is decreased by a small value. This results in both a reduction of the noise contained in the image and the number of pixel intensities represented in the image. Segmentation that follows smoothing has no differences from the standard procedure described earlier.

However, smoothing and segmentation by themselves do not produce the segmentation we want. The desired outcome is achieved by adding PCNN-output binary images until we stop the addition manually. As a result, the only point where manual intervention is necessary is an evaluation of binary images to select the best one. If a priori information about application is available (for example, proportions of different elements in composite), then the whole process of image segmentation can be automated.

2. SEGMENTATION OF HETEROGENEOUS MATERIALS

We consider a specific example from material science. Material scientists which are interested in the modeling of cellular solids (foams) very often perform hydrodynamic model calculations to learn more about highly dynamic, cyclic, and non-equilibrium-inducing loading conditions involving large strains and high strain rates. [5] The initial conditions of the hydrodynamic model calculations require very accurate input data from, e.g., micrographs, which are two-dimensional black-and-white images of cross sections of such materials. Details such as cell dimensions, shapes, ellipticities, orientations, strut/wall thicknesses, material defects, etc. can only be extracted from high-level image processing algorithms reliably if a proper quality of low-level image processing, i.e., smoothing and segmentation, is performed. For the sake of illustration, we shall demonstrate image smoothing and segmentation for a polymeric foam as shown in Fig. 3. [5]

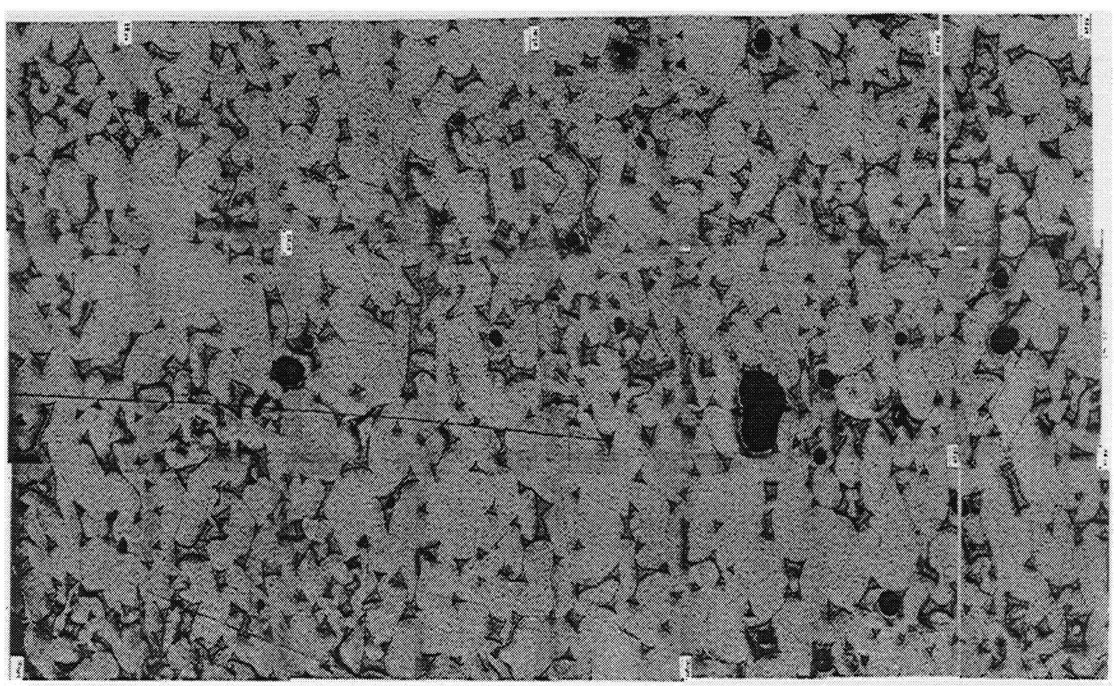

Fig. 3. Original image.

3. RESULTS

The overall segmentation approach we use to segment images of materials consists of three stages. First, an original image is denoised using PCNN smoothing. Second, the denoised image is segmented using PCNN. Finally, the output binary images produced by segmentation are added until an image of quality that is acceptable for a given application is obtained.

The original image after applying PCNN-based smoothing is shown in Fig. 4. The visible difference between the smoothed image and the original image is not too drastic. However, it is obvious from their histograms, shown in Fig. 5, that the spatial variance that existed in the original image was reduced. Smoothing can be stopped after selected criteria are met. In our case we stopped smoothing after performing 100 PCNN iterations over the whole image. Smoothing used parameter settings of $\beta = 0.01$, $\alpha_L = 1.0$, $\alpha_\Theta = 5.0$, $V_F = 0.5$, $V_L = 0.2$, $V_\Theta = 1.0$, and there was no leaky integrator in the feeding channel of PCNN. The corresponding linking weights template is

$$W = \begin{bmatrix} 1 & 1 & 1 \\ 1 & 0 & 1 \\ 1 & 1 & 1 \end{bmatrix} \qquad (2)$$

We checked the influence of global inhibition on the quality of segmentation. It was found it did not impact the results. The only difference was in the ordering and grouping of output binary images. [6] Also, variation in setting of the parameters for a PCNN segmentation (we varied β) did not produce different results, indicating that this kind of variation could be eliminated in our specific application problem.

Fig. 6 shows the statistics for the number of adjustments of pixel intensities over time for one of the PCNN smoothing runs. We can see that it is almost a monotonic decrease. This decrease provides a possible criterion for halting smoothing that is different from the one we had; for example, the number of adjustments relative to the size of the image could be used as a criterion to halt smoothing.

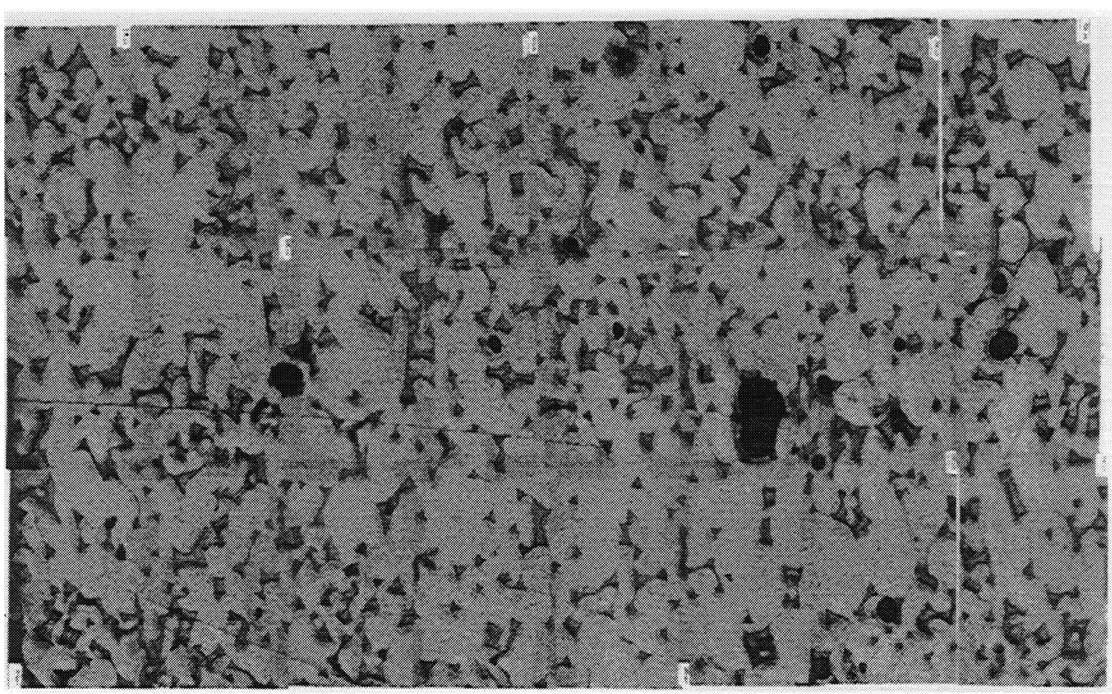

Fig. 4. Original image after smoothing.

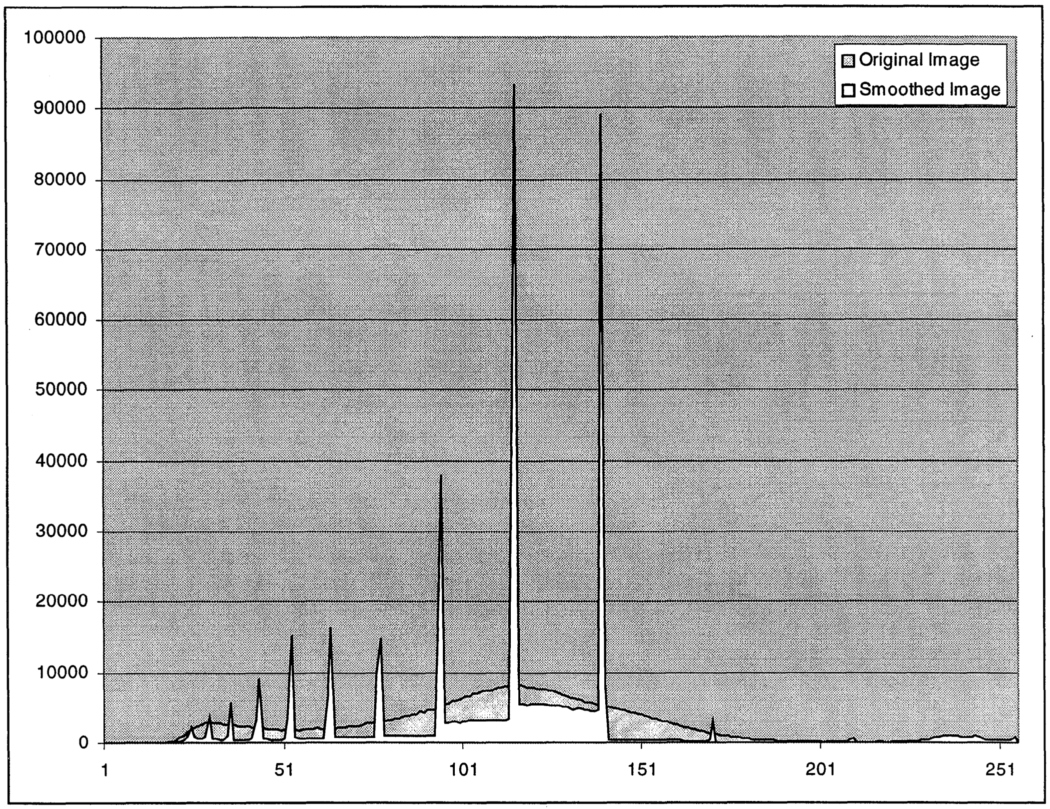

Fig. 5. Histograms of the original image (shown in Fig. 3) and the smoothed image (shown in Fig. 4).

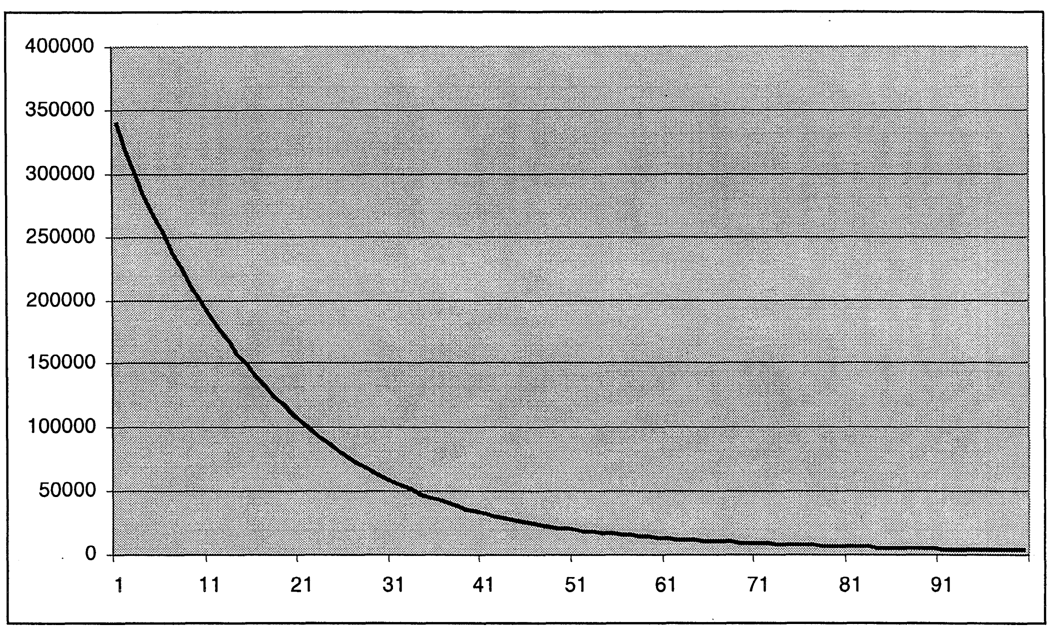

Fig. 6. Number of pixel intensity adjustments over smoothing iterations.

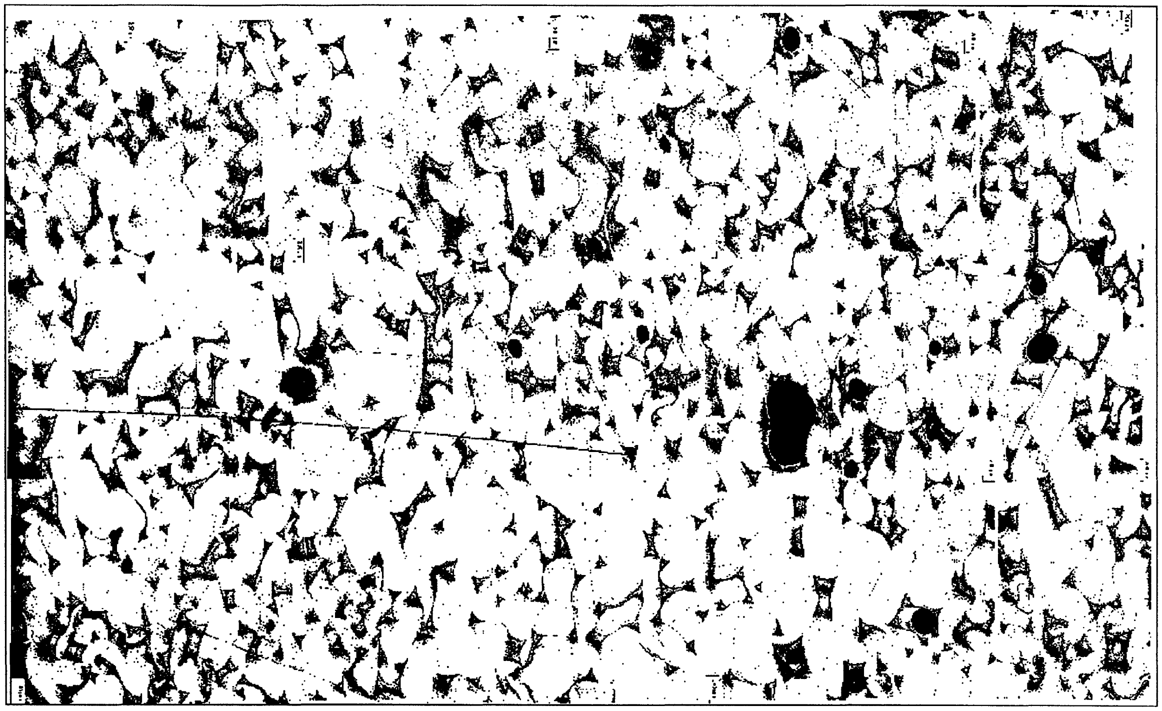

Fig. 7. Original image segmentation using PCNN. No preliminary smoothing was applied.

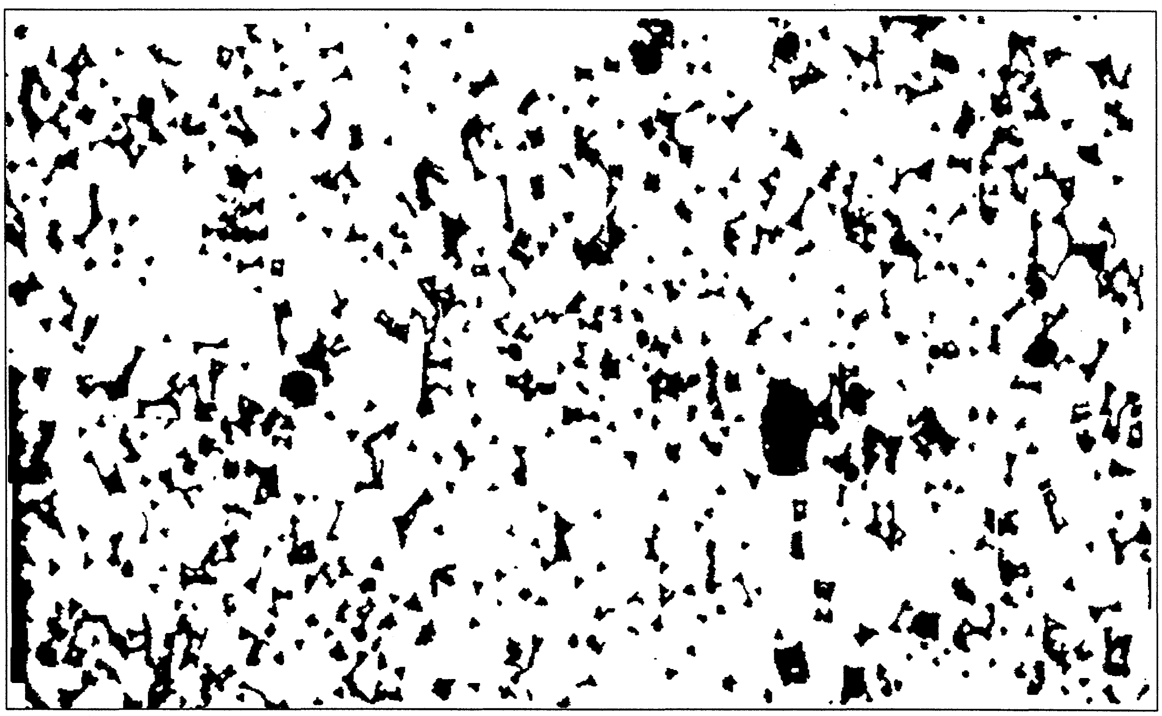

Fig. 8. Segmentation after smoothing was applied to the original image.

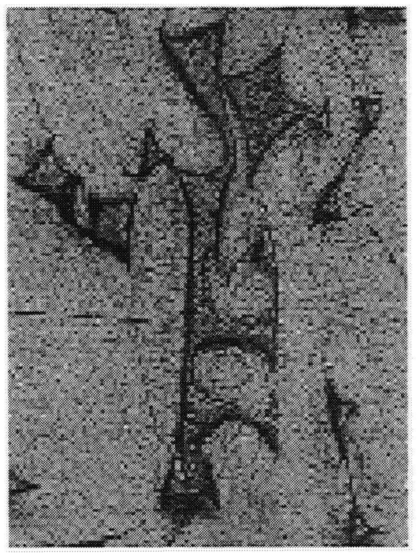

Fig. 9. Subregion of the original image shown in Fig. 3.

Fig. 10. Subregion of the smoothed image shown in Fig. 4.

Fig. 11. Segmentation results for the region shown in Fig. 9. No smoothing is applied.

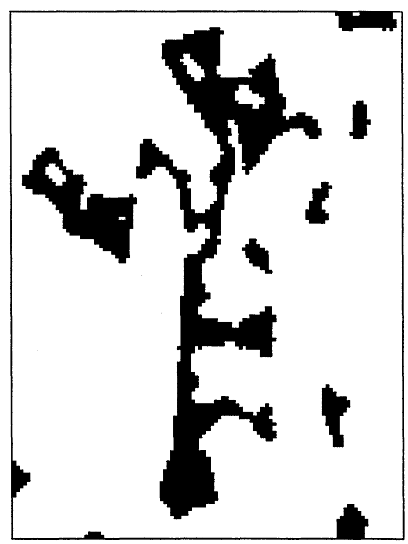

Fig. 12. Segmentation results for the region shown in Fig. 10. Smoothing is applied before segmentation.

The results corresponding to the segmentation without preliminary smoothing and with preliminary smoothing are shown in Fig. 7 and Fig. 8. Figures 10, 11, 12 show the results of processing one small subregion from the original image, shown in Fig. 9. As we can see from the images, the PCNN smoothing provides less noisy segmentation and does not result in blurring the image.

Segmentation is followed by application of a geometric filtering algorithm, which extract statistics of material features to support automatic optical analysis and evaluation of material structure. [7,8.]

4. CONCLUSIONS

We have shown that the pulse-coupled neural network is a useful tool for image preprocessing such as image denoising and segmentation. Integration of smoothing, segmentation, and addition of output binary images enabled us to automate the process of processing images of granular materials. Manual intervention was only necessary to select which image among those generated was the best. The segmentation by itself was performed automatically. Further research will explore comparison of PCNN smoothing aimed at N-ary segmentation and wavelets segmentation.

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